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Title: BIG DATA HEALTH PHYSICS: A CASE STUDY IN OPERATIONAL HEALTH PHYSICS

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BIG DATA HEALTH PHYSICS: A CASE STUDY IN OPERATIONAL HEALTH PHYSICS

BY

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This report is prepared to satisfy the class requirements of PHYS 597 Reading & Special Problems. This study includes a special project in radiation protection, and it is written in a format consistent with the requirement of a master's thesis

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CHICAGO, ILLINOIS

2 January 2020

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ABSTRACT

This paper, written as a two part project as required by Illinois Institute of Technology's Phys597 Reading & Special Problems class and health physics professional master's program, focuses on the results of a prototype data collection process implemented at a Los Alamos National Laboratory facility. In particular, this paper examines the data in a statistical context in an effort to optimize operational health physics processes at the Los Alamos National Laboratory.

INTRODUCTION

In an effort to optimize the operational health physics program at a facility in the Los Alamos National Laboratory, a prototype data analytics process was established that combined several data flows into a single comprehensive program in an effort to more effectively monitor the performance of the program. Health physics, the study and application of radiation safety, plays a critical role at the Los Alamos National Laboratory (LANL). As the senior laboratory in the Department of Energy system, much of LANL's mission focuses around the use of radioactive materials. The LANL health physics program is consistently called upon to support the safety of workers and the public in the management of safe usage of radioactive materials.

Like most health physics programs in the U.S., LANL maintains several metrics which monitor certain aspects of the program. These metrics focus mostly on the occurrence of safety events. Examples of these events include worker contamination, area contamination etc. that are used as key performance indicators. Historically and across several RP related industries, the creation and maintenance of these metrics has been time consuming and limited in scope. In light of the availability of new technology and health physics software, new avenues for the easy collection of data creates opportunities to look at health physics programs in a less traditional and more holistic approach.

In May 2018, a fledgling program in data analytics was established to look at combining three major data flows. These include the work performance of RCTs (introduced in this paper), the issues encountered (which had been previously established), and instrumentation usage. This paper, written as the first of a two part project, looks specifically at applying elementary statistical concepts to analyze the data as a case study. The concepts, as employed in this paper, are consistent with the level of IIT's Math 525 Statistical Models and Methods (a statistics class for non-mathematics majors). The statistical tools available at this level are limited and full implementation of a data analytics program like the one described in this paper would require deeper sophistication in the tools and techniques selected.

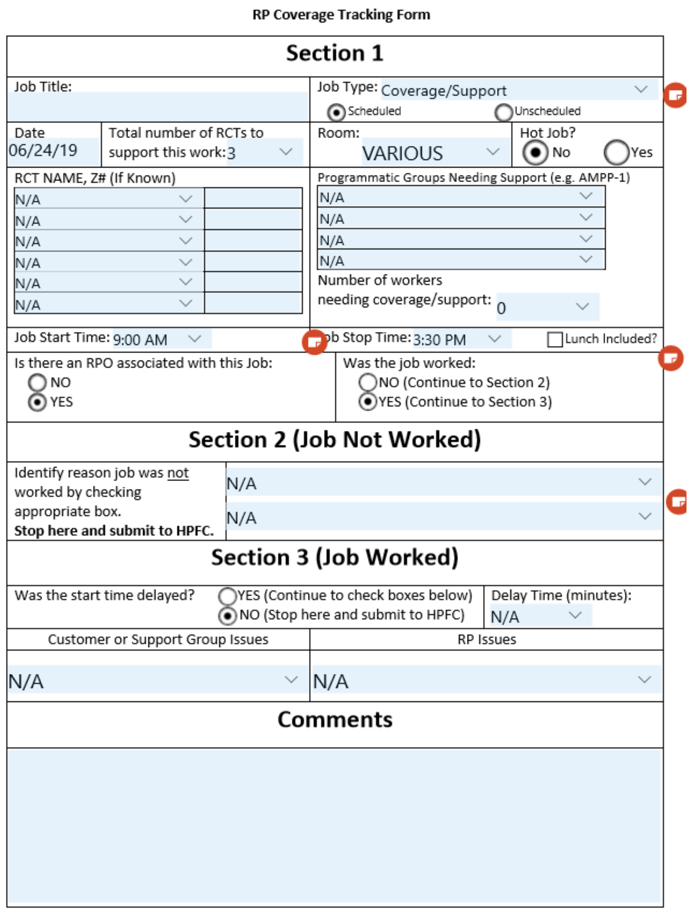
However, upon discussion with IIT’s graduate health physics program, it was believed there would be value added by making the attempt as kind of crude first attempt at a proof of concept rather than polishing a finished product. This paper details a very basic statistical analysis to a very new approach to managing a health physics program.

BACKGROUND

Work Performance Data Collection:

Prior to May 2018, work performed at a facility in LANL had been documented using paper forms. Work performed by RCTs (typically referred to as job coverage) involves an RCT being present while some job is being performed. Examples include breaching a pipe containing radioactive material, performing maintenance on engineering barriers such as gloveboxes, opening of containers containing radioactive materials, etc. The intent of maintaining paper forms to record work was to be able to be able to count the number of hot jobs (jobs involving the wearing of respirators) at the end of the month. The paper forms were cumbersome and it would be time consuming to collect data using this process.

In November of 2018, an electronic form using PDFs was created as a simple electronic version similar to the paper copy (shown in Figure 1). Starting in May 2018, the management expectation was that an RCT would be scheduled to perform work at a particular time, the work would be performed, and finally the work would be captured on a pdf form. Per RP management, it is the responsibility of the RCT to fill out a form for every time RCT coverage was provided in order to provide the most accurate representation of the RP’s efforts. Items of interest that were captured include whether the work was scheduled/unscheduled, start/stop times, if the work was delayed, etc. The electronic forms were saved and the data was automatically compiled into a monthly spreadsheet. The final product was a weekly report written to senior management regarding the work performed.


RP Coverage Tracking Form

Section 1

Job Title:

Job Type: Coverage/Support

Scheduled / Unscheduled

Date 06/24/19 | Total number of RCTs to support this work: 3 | Room: VARIOUS | Hot Job? No / Yes

RCT NAME, Z# (If Known)

N/A
N/A
N/A
N/A
N/A
N/A

Programmatic Groups Needing Support (e.g. AMPP-1)

N/A
N/A
N/A
N/A

Number of workers needing coverage/support: 0

Job Start Time: 9:00 AM | Job Stop Time: 3:30 PM | Lunch Included?

Is there an RPO associated with this Job: NO / YES

Was the job worked: NO (Continue to Section 2) / YES (Continue to Section 3)

Section 2 (Job Not Worked)

Identify reason job was not worked by checking appropriate box.
Stop here and submit to HPFC.

N/A
N/A

Section 3 (Job Worked)

Was the start time delayed? YES (Continue to check boxes below) / NO (Stop here and submit to HPFC)

Delay Time (minutes): N/A

Customer or Support Group Issues: N/A

RP Issues: N/A

Comments

Figure 1: Example of Coverage Tracking Form

From May 2018 through April 2019, 3554 entries were made describing the work performance in the field by thirty-six RCTs. The following graph in Figure 2 displays the total number of entries in this period. It should be noted that an entry represents the submittal of a tracking form. Most forms are for work completed and some represent work that was cancelled, delayed, etc. This graph could be best described as total anticipated work in the May 2018 and April 2019 time period.

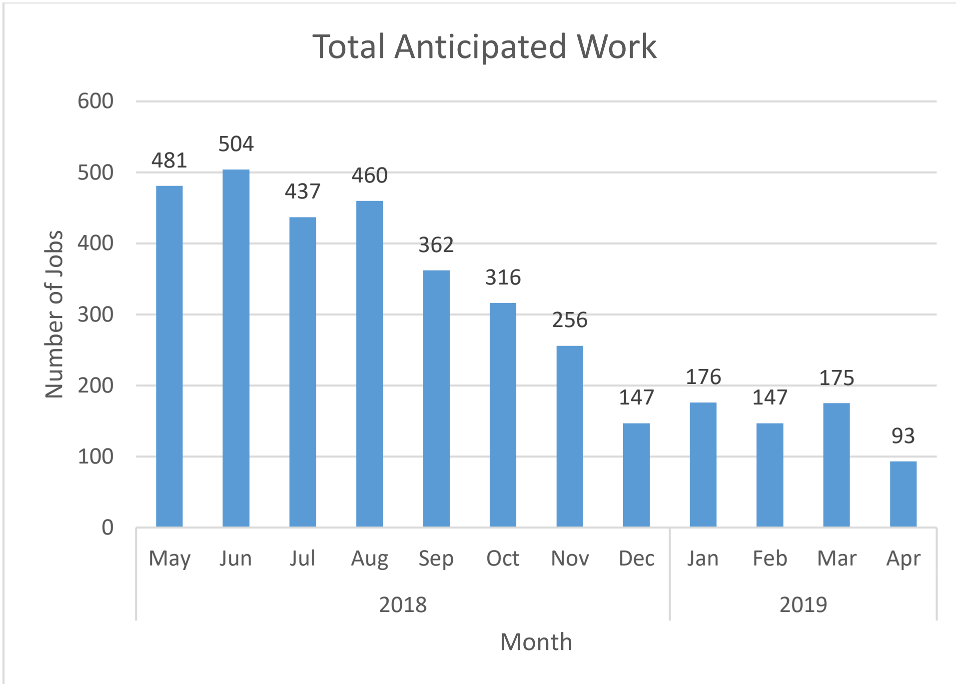


Figure 2: Total Anticipated Work

Radiation Protection Issues:

As mentioned, radiation protection issues are metrics maintained by the LANL health physics group which act as indicators of the performance of the program. These metrics focus mostly on the occurrence of safety events. Examples of these events include worker contamination, area contamination etc. Typically, an issue recognized one of several ways. Most commonly, they are encountered while work is performed by RCTs in the field. A formal procedure exists that identifies thresholds for which a notification of such an event must be made. This communication occurs through a LANL application called Radiation Protection Initial Notifications (RPINs). A form is filled out and the notification is sent to the appropriate group of specified people. The application also maintains a simple database. Monthly, the database is accessed by the operational health physicist where the individual notifications are complied, analyzed, and divided into separate metrics and maintained as control charts.

From 2018 through April 2019, 277 notifications were made describing the issues encountered in the facility. The following graph in Figure 3 displays the total number of entries in this period.

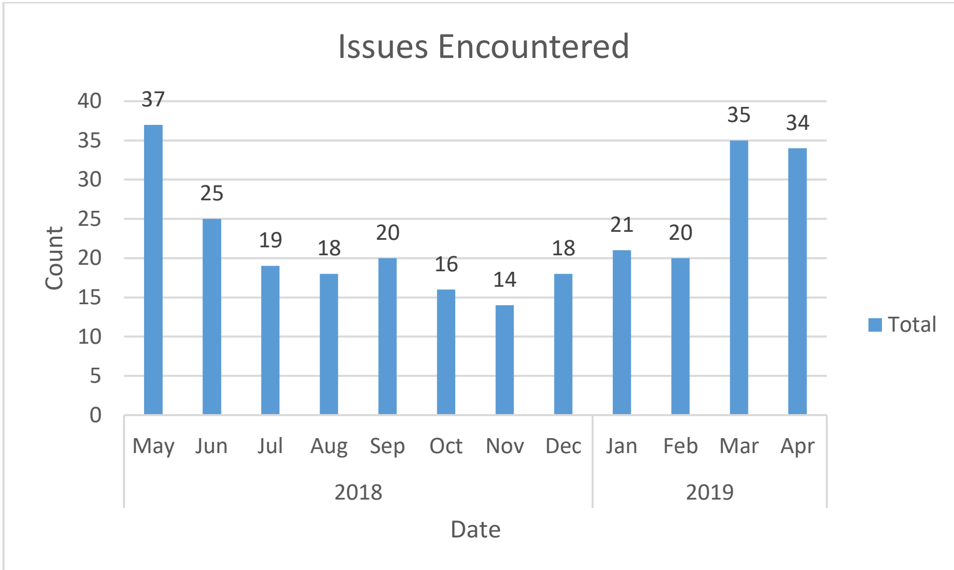


Figure 3: Issues Encountered

Instrument Usage:

Data regarding instruments usage comes from a database created for Visual Survey Data System radiological survey software. The software is used to create the forms used by the RCTs to create the documentation necessary to describe the work performed (a radiological survey). This database maintains all of the information regarding the surveys written and can provide several opportunities in the future to use in a data analytics program. However, we are particularly interested in instrument usage since the calibration, maintenance, and usage of radiological instruments is expensive. In addition, many facilities do not have a systematic way of establishing the need for instrumentation.

From 2018 through April 2019, a radiological instrument was used 7263 times per the VSDS software database. It should be noted that a significant portion of the instrumentation used is not recorded in the job tracking forms since much of the work is routinely performed and was not initially of interest to the facility. This is a weakness in the data analytics program and will be discussed in more detail later. The following graph in Figure 4 displays the total number of instrument entries in the period.

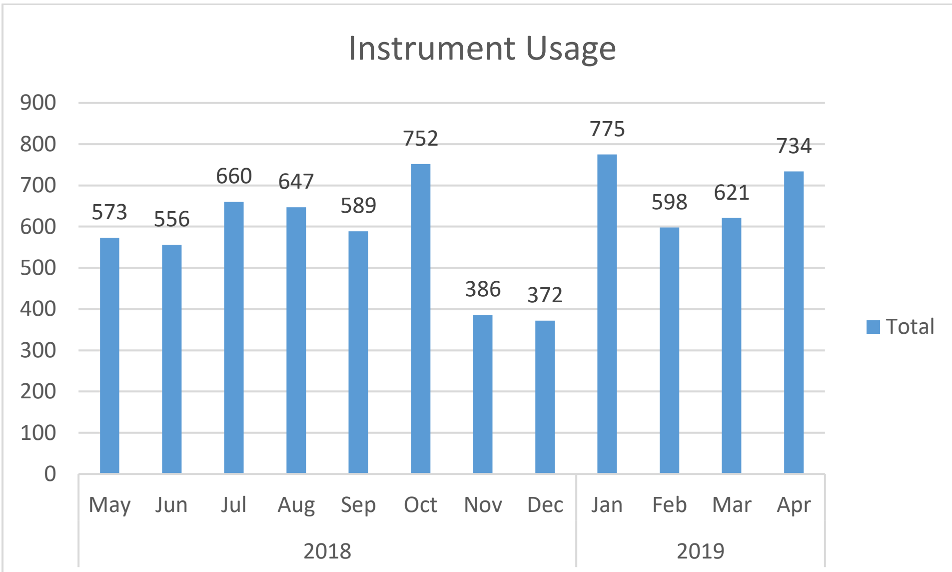


Figure 4: Instrument Usage

Note: Because of a limited amount of time to complete this project the level of difficulty managing instrumentation data in a usable form, no analysis will be performed in this paper regarding instrument usage.

Work Performance

Anticipated Work Performance

Between May 2018 and April 2019, 3554 entries were made regarding the anticipated performance of work. As discussed, this number represents all work that is anticipated in being performed in the facility. It consists of all entries into the system regardless of whether the work was scheduled, unscheduled, hot work, cancelled, etc. It is a strong candidate for analysis since it is a good indicator of the gross work load in the facility. Regarding a basic statistical analysis, approaches were used that look at measures of center.

Based on the data, 245 days were recorded as working days. One of the limitations of this process is that it is possible that there were working days where work did not occur. For example, if on January 1st the facility was available to have work performed and no work was anticipated to be performed, then there is no mechanism in the system that would record such an event. However, based on experience working in this facility, this event would be exceedingly rare and (to my knowledge) has never occurred within the facility in the period evaluated.

In Figure 5 below, we show the work anticipated on a daily basis. We compute the mean to be 14.51 jobs per day supported by an RCT in the facility's health physics program.

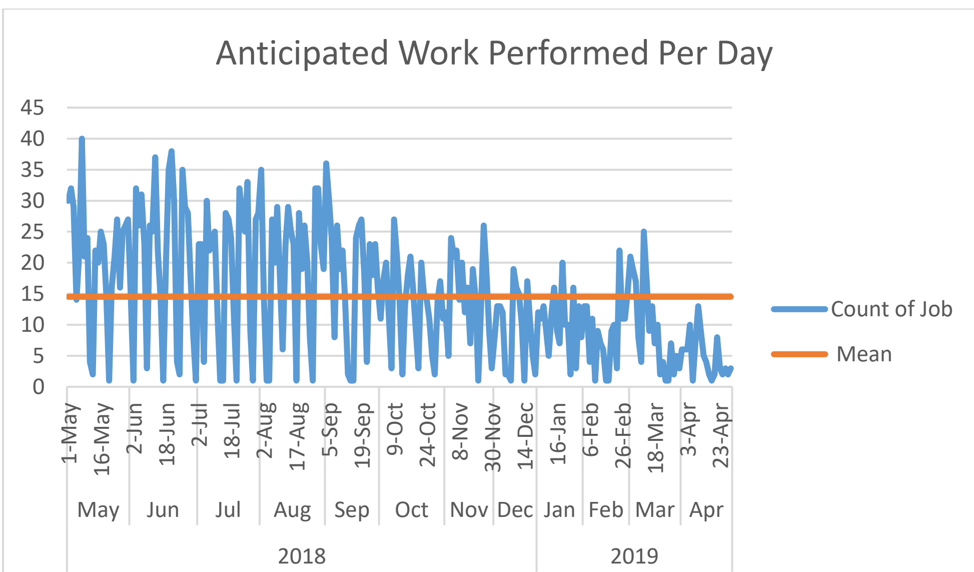


Figure 5: Anticipated Work Performed Per Day:

Comparing the mean to other values of center as shown in Figure 6, we expect to see values close to the mean suggesting the data is well centered. We see this to some degree regarding the median with a value of 14. The median represents the "middle" value if we were to list the data from decreasing to increasing. However, looking at value assessed for mode, we see a significant difference from the mean (14.51 vs. 1). The value of mode is the value that was input into the job tracking sheets most frequently. Finally, we compute the value of standard deviation for the data. Although the calculated values for sample standard deviation and population standard deviation are computed to be close (10.00 vs. 9.99), the population standard deviation is chosen since the all work within the facility is assumed to have been represented in the data collection process.

Measures of Center	
Mean	14.51
Median	14
Mode	1
Standard Dev (Pop.)	9.99

Figure 6: Anticipated Work Performed Per Day Measures of Center

Since many of the concepts introduced in Math 525 are dependent on a Normal distribution, an effort is made below to compare these results to this ideal distribution. Using the computed standard deviation and the computed mean, we can try to graphically compare the data to the expected values. In Figure 7 below, the values are organized in terms of their frequency with respect to the standard deviation.

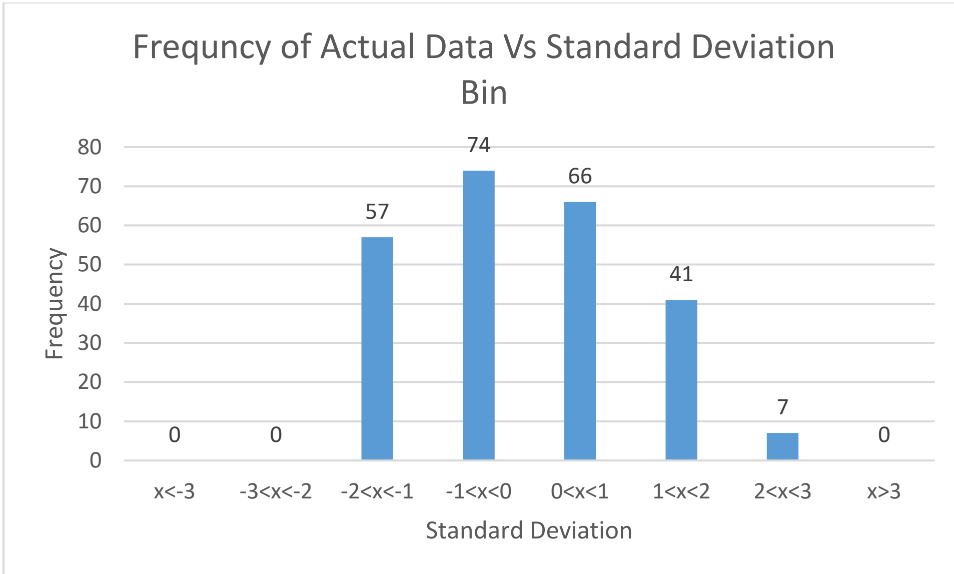


Figure 7 Frequency of Actual Data Vs Standard Deviation Bin

Following this, we compare the values above in terms of their relative frequency to a simulated normal distribution.

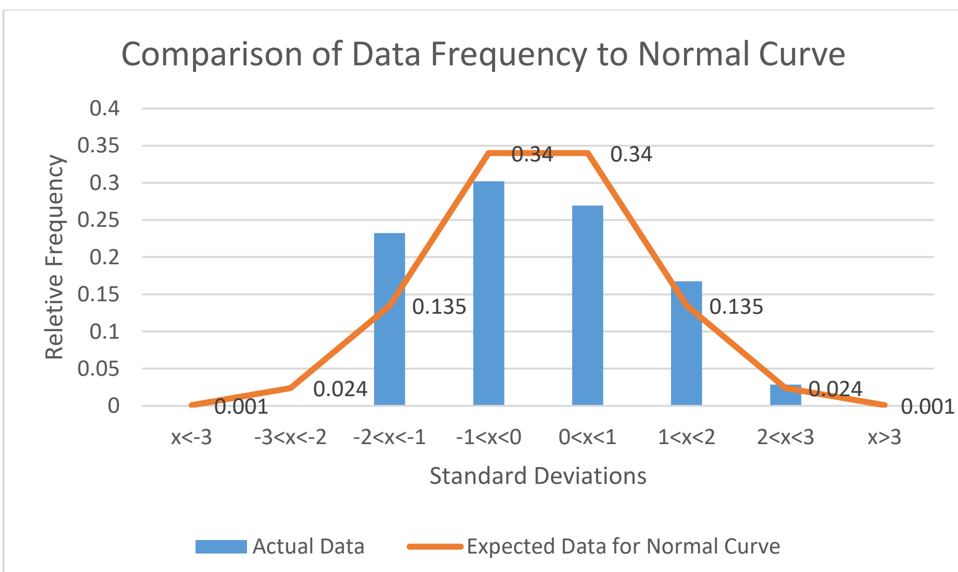


Figure 8: Comparison of Data Frequency to Normal Curve

Based on the graph in Figure 8, it can be seen that we are somewhat limited to the fact the data does not match a normal curve as desired. Since we are going only as far as Math 525 (a fairly basic math course), we will continue with the analysis of the other relevant material for the sake of completing the independent study within the appropriate time frame. Realistically though and given more time, this would most likely be a point where we would choose a more sophisticated approach to statistical modelling.

Work Actually Performed

Following the discussion above regarding anticipated work and acknowledging some limitations regarding the data set, the obvious next data sets to analyze include work that was actually performed. Between May 2018 and April 2019, 3093 (87%) of entries were made regarding the actual performance of work. This number represents all work that is actually in being performed in the facility. It consists of all entries into the system regardless of whether the work was scheduled, unscheduled, hot work, etc. so long as the work was not cancelled, rescheduled, etc. It is a strong candidate for analysis since it is a good indicator of the net work load in the facility. Again, regarding a basic statistical analysis, approaches were used that look at measures of center.

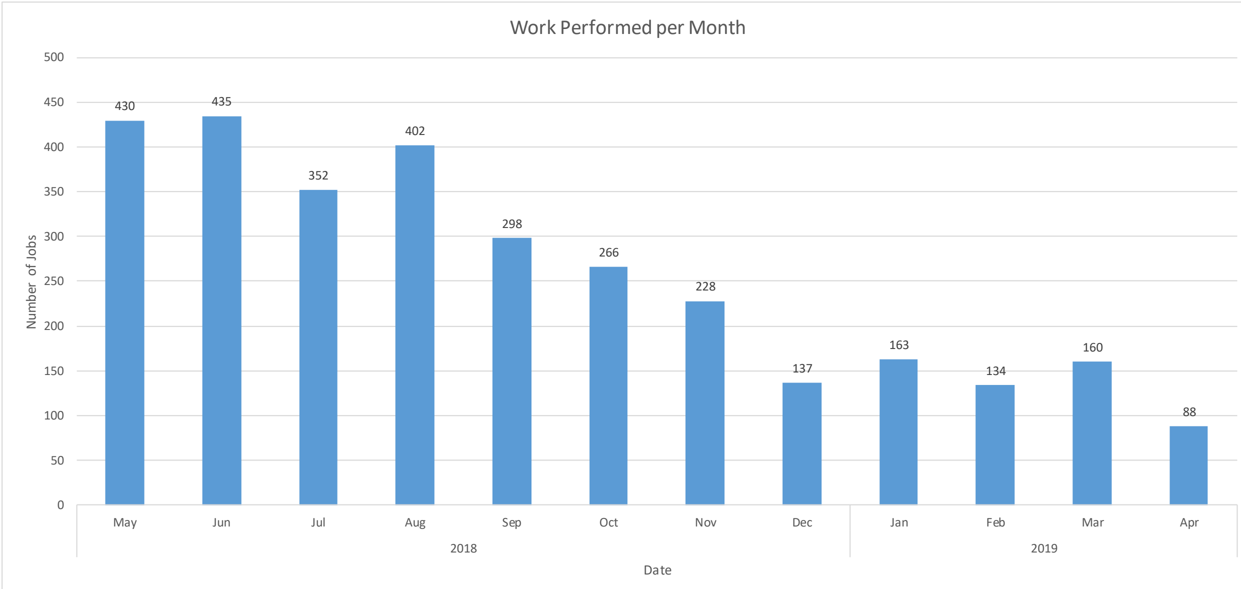


Figure 9: Work Performed per Month

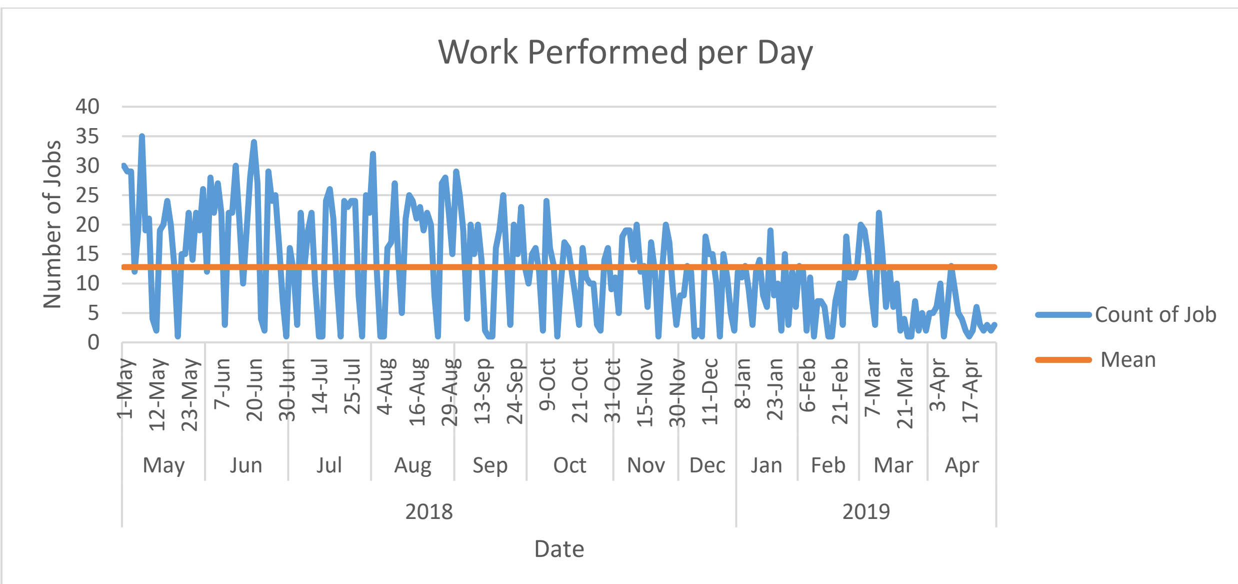


Figure 10: Work Performed per Day

The mean amount of work is computed to be 12.78. Comparing the mean to other values of center as shown in Figure 6, we expect to see values close to the mean suggesting the data is well centered. We see this to some degree regarding the median with a value of 12. The median represents the "middle" value if we were to list the data from decreasing to increasing. However, looking at value assessed for mode, we see a significant difference from the mean (12.78 vs. 1). Finally, we compute the value of standard deviation for the data to be 8.52.

Measures of Center	
Mean	12.78
Median	12
Mode	1
Standard Deviation (Pop.)	8.52

Figure 11: Actual Work Performed Per Day Measures of Center

Determining Whether the Work Actually Performed is Adequate

Total Work Performance: One of the core goals for initiating the big data health physics programs is to establish that work being performed to support the facility is being completed. The following methods show that anticipated work involving radiological control technicians is being completed.

Using that data as described above, it was determined that 87% of jobs entered are completed as expected and 13% of jobs entered into the system were not worked. Using a 0.05 significance level, we test the claim that more than vast majority (85%) of jobs performed this past week have been worked. In order to test a claim regarding a proportion, three requirements must be satisfied (Triola, 2006):

- The sample data used is random
- Conditions of a binomial distribution are satisfied
- Conditions of $np>=5$ and $nq>=5$ must be satisfied to approximate using a normal distribution

Claim: More than vast majority of jobs performed this past week have been worked ($p>0.8$).

It will be assumed that the data, collected using the data collection methods described in this paper, represents a random sample. A binomial distribution is assumed with jobs worked representing "success" and jobs not worked representing "failure". Finally, it can be shown that np>=5 is satisfied with n=3554, p=0.85, and q=0.15. Thus, we satisfy our requirements. We will assume that a normal distribution is approximated.

Based on our claim above, we select our null and alternative hypothesis to be the following: H_0: p=0.85 and H_1: p>0.85. To compute the z statistic, we have the following (Triola, 2006):

$$z = \frac{\hat{p} - p}{\sqrt{\frac{pq}{n}}} = \frac{0.87 - 0.85}{\sqrt{\frac{0.85 * 0.15}{3554}}} = 3.34$$

Based on the table A-2, Standard Normal (z) Distributions: Cumulative Area from the LEFT, provided in the text, a P-Value of 1-.9996=0.0004<0.05 allows us to reject our null hypothesis. It can therefore be concluded that there is sufficient sample evidence from the Big Data Health Physics Program to support the claim that the vast majority of work involving RCTs is being completed.

Hot Work Performance: All work performed by RCTs is significant in some way or another. Of particular importance is hot work where a respirator is worn by the RCT and other workers in the room. This work is of particular interest to the radiation protection department as well as the facility it supports since this work tends to be higher risk and usually higher value.

From the data collected, 779 entries were made where a hot job was anticipated. Of those entries, 650 hot jobs were worked and 129 were not. Using that data, it was determined that 83% of jobs entered are completed as expected and 17% of jobs entered into the system were not worked. Using a 0.05 significance level, we test the claim that more than vast majority (85%) of hot jobs performed this past week have been worked. In order to test a claim regarding a proportion, three requirements must be satisfied:

- The sample data used is random
- Conditions of a binomial distribution are satisfied
- Conditions of np>=5 and nq>=5 must be satisfied to approximate using a normal distribution

Claim: More than vast majority of jobs performed this past week have been worked (p>0.85).

It will be assumed that the data, collected using the data collection methods described in this paper, represents a random sample. A binomial distribution is assumed with jobs worked representing "success" and jobs not worked representing "failure". Finally, it can be shown that np>=5 is satisfied with n=779, p=0.85, and q=0.15. We will assume that a normal distribution is approximated. Thus, we satisfy our requirements.

Based on our claim above, we select our null and alternative hypothesis to be the following: H_0: p=0.85 and H_1: p>0.85. To compute the z statistic, we have the following (Triola, 2006):

$$z = \frac{\hat{p} - p}{\sqrt{\frac{pq}{n}}} = \frac{0.83 - 0.85}{\sqrt{\frac{0.85 * 0.15}{779}}} = -1.56$$

Based on the table A-2, Standard Normal (z) Distributions: Cumulative Area from the LEFT, provided in the text, a P-Value of 0.0594>0.05 does not allows us to reject our null hypothesis. It cannot therefore be concluded that there is sufficient sample evidence from the Big Data Health Physics Program to support the claim that the vast majority of hot work involving RCTs is being completed. Hot work, as performed by RCTs in this facility, should be analyzed further for optimization.

Applying Work Performance Models to Issues Occurring in the Field

Choice of Model

In the following section, we attempt to apply the work performance models as described above to optimizing work performed in the field. A few different approaches were taken in organizing the data to look at trends in the work being performed. As shown below in Figure 12, several models were experimented with and the one that seems to be the most effective at looking at trends was modeling work in terms of days in a week (Monday, Tuesday, etc.). This was actually surprising but not necessarily unintuitive since a “week” model is typically the basic unit of scheduling at the facility. Projects that are performed typically start on Mondays and end on Thursdays. Looking at the work in terms of that cycle seemed to yield the most interesting results.

There are two items worth mentioning with regard to cycles. Firstly, the review period for this project occurred over exactly one year. However, if this project occurred over several years, it is very likely based on experience working in the facility that the work performed in the year occurs in a cycle with most of the work being performed in the spring and summer and less work being performed in the fall and winter. In the case we have that longer sampling period, using a yearly cycle would be a strong modelling choice. Second, it is worth mentioning that many facilities that perform radiological work do not work off a weekly or monthly cycle. Nuclear power stations are an example of that where work is performed in terms of an outage schedule and care should be taken in how data is modelled.

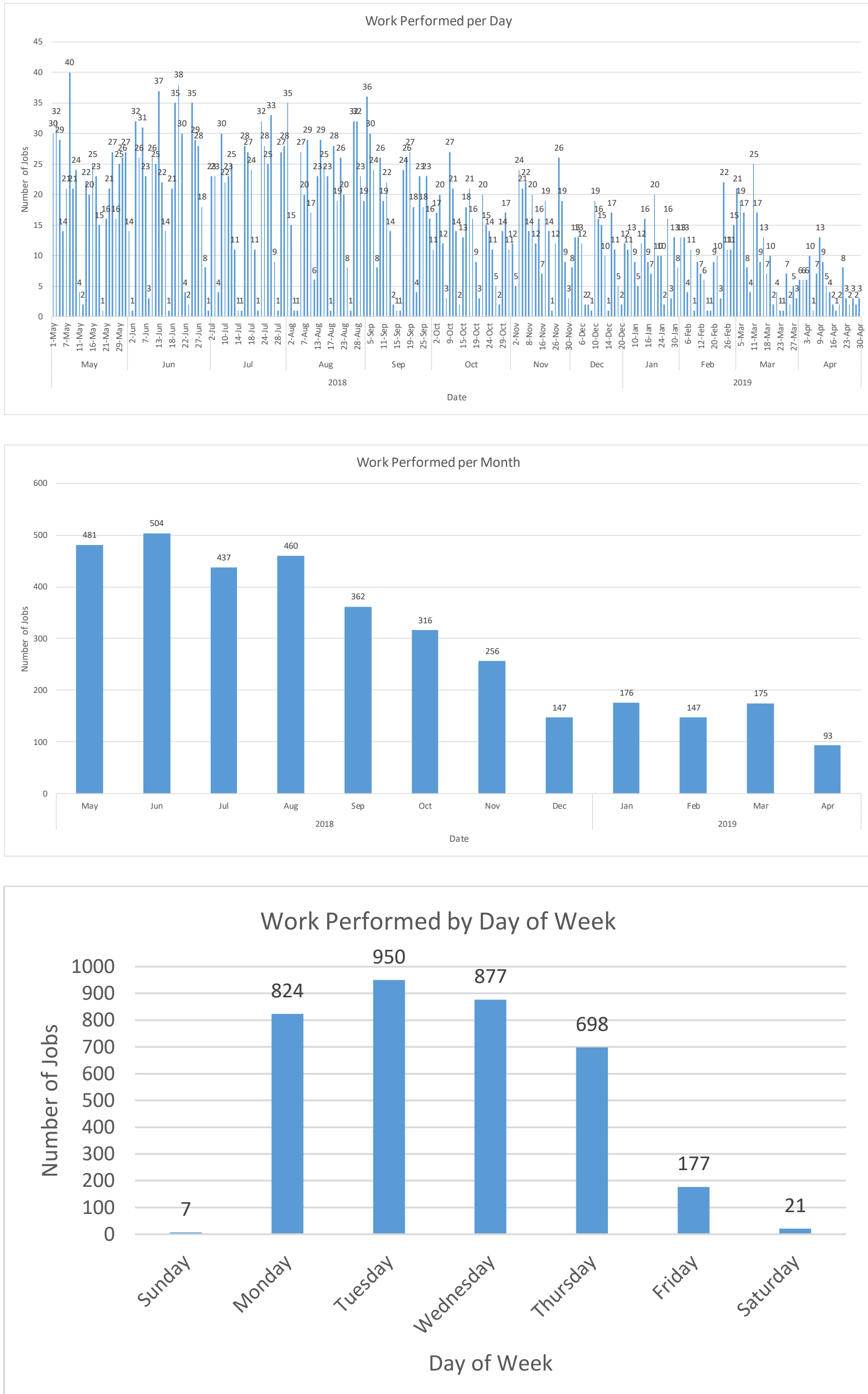


Figure 12: Models of Anticipated Work (Day, Month, Day of Week)

Where the Day of Week Model Applies

In the next few paragraphs, we evaluate the models based on the day of the week the work was anticipated to be performed. In this effort, we apply linear correlations as described in the Triola text as described in the equation below:

$$\text{Correlation } r = \frac{n\Sigma xy - (\Sigma x)(\Sigma y)}{\sqrt{n(\Sigma x^2) - (\Sigma x)^2}\sqrt{n(\Sigma y^2) - (\Sigma y)^2}}$$

Equation 1: Linear Correlation r (Triola, 2006)

It is without a doubt that we would expect to see strong correlations in the models since we intuitively understand that when more work is occurring, there is greater opportunity for it to be cancelled, more opportunities for problems to occur, etc. However, it is important to look at these models first to establish the validity of the "day of the week" model before moving to models where this model does not apply. Where this model does not apply provides an opportunity for investigation and targeted optimization.

Jobs Worked Vs Jobs Not Worked

In the case below, we look at a comparison of jobs being worked vs. the jobs that are not be being worked e.g. cancelled, rescheduled, craft workers not showing up, RCTs not showing up, etc. As shown below in Figure 13. We have calculated our linear correlation coefficient to be 0.964 which indicates a very strong positive correlation. As mentioned, this should come as no surprise. This graph simply indicates that work is generally performed Monday through Thursday with the maximum occurring on Tuesday and the minimum occurring on Sundays. The rate at which a job is not worked ranges from 0% (Sundays) to 19.6% (Fridays).

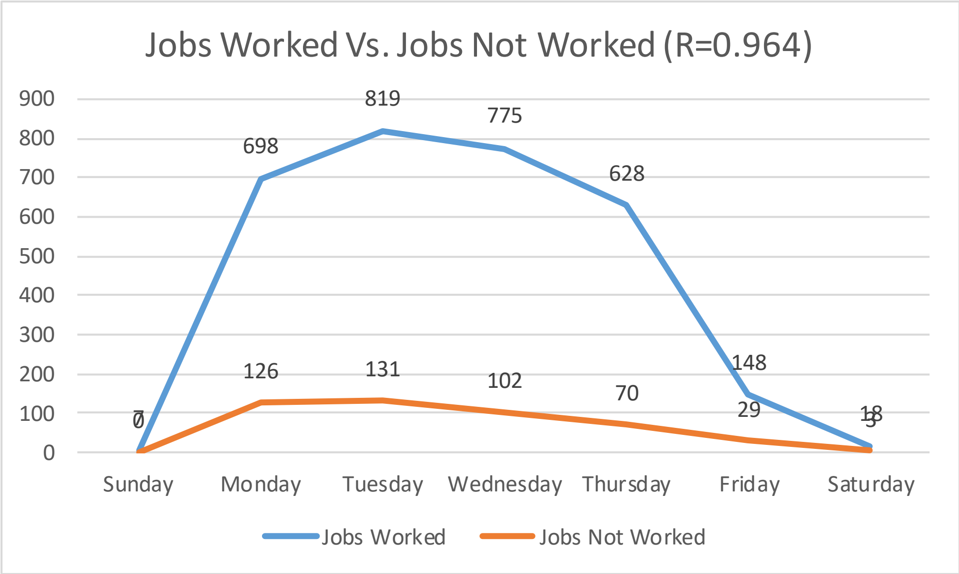


Figure 13: Jobs Worked Vs. Jobs Not Worked

Jobs Worked Vs Personnel Contamination

Applying our work models to look specifically at radiological aspects of the facility, we compare the work actually being performed to how often workers are becoming contaminated. Worker contamination occurs when some radioactive material (particle, dust, liquid, etc.) unintentionally comes in contact with a radiological worker. It is of particular importance to the health physics organization since it is a key indicator of the health of the facility. Again, there are no surprises here. In Figure 14, there is a fairly strong positive correlation of R=0.904. This suggests that as more work is performed, more workers become contaminated.

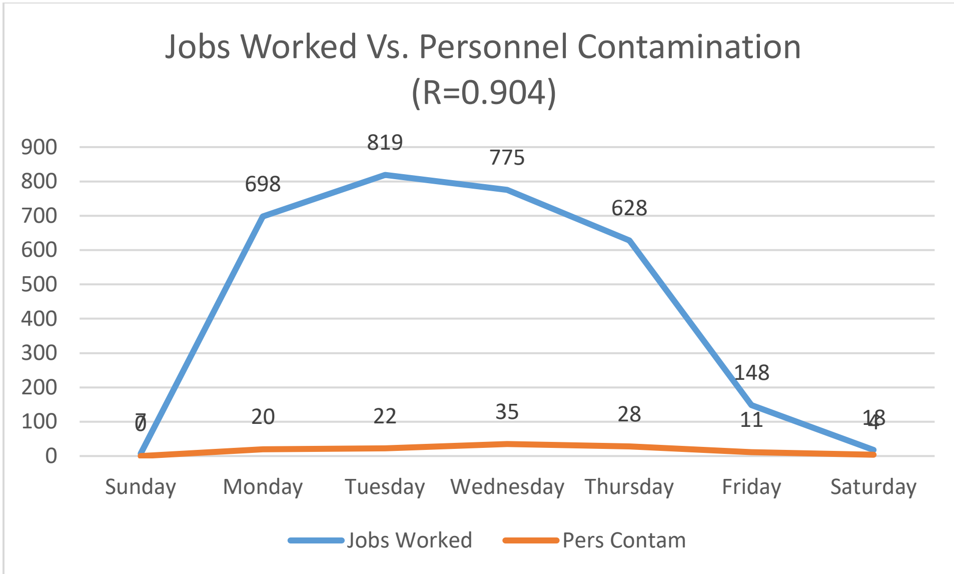


Figure 14: Jobs Worked Vs. Personnel Contamination

We can actually improve upon this model by specifically looking at hot work being performed in the facility as compared to personnel contamination occurring. As shown in Figure 15 below, Hot work, higher risk work that requires a respirator, tends to occur more towards the middle of the week (as opposed to non-hot work that tends to occur earlier in the week as suggested in the previous figure). This may be due to the fact that hot work tends to require more preparation. Regardless, when we compare it to radiological problems occurring in the facility like personnel contamination as shown below, we see an even stronger correlation with R=0.977. Again, hot work tends to be associated with higher risk of exposure to radioactive materials so there is nothing surprising about this relationship.

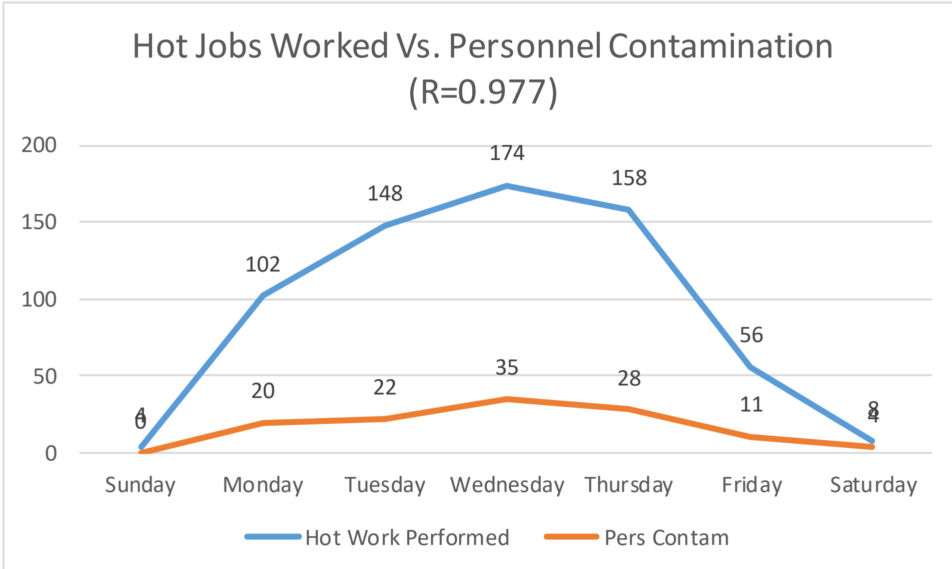


Figure 15: Hot Jobs Worked Vs. Personnel Contamination

Where the Day of Week Model Does Not Apply

As shown above, the "day of the week" model applies to a very wide range of metrics both in terms of how work is performed and radiologically how issues tend to occur. The examples highlighted are only a few of many that were explored and validated this model. In an effort to not belabor this point, we want to talk about where this model does not hold using linear correlations. Below in Table 1 is a small sample of the correlations analyzed. Most were unsurprisingly correlated to the work performed. Examples like false alarms on continuous air monitors (CAMs) showed no correlation between work being performed and that is unsurprising since false alarms seem to occur randomly. We would like to spend some time looking at a few of the more surprising metrics.

Metric Compared to Jobs Worked	Linear Correlation R
Jobs Worked	1.00
Jobs Not Worked	0.96
Hot Work Performed	0.94
Jobs Delayed	0.98
Customer No Show	0.73
Customer Not Ready	0.96
Total Issues	0.92
Pers Contam	0.90
First Opprotunity	0.88
Exit RBA	0.85
Exit RCA	0.65
True CAM	-0.23
False CAMs	0.07

Table 1: Sample of Metrics Analyzed for Model Correlation

Jobs Worked Vs Customer No Shows

A "Customer No Show" occurs when RCT shows up to cover work and, without notification, the workers do not show up to perform the work. This is an enormous problem and is incredibly costly. The availability of RCTs is very often a bottleneck for the ability to perform work in the facility. By not showing up to perform work, not only is that work group's work not performed, but also the ability to perform another job instead is taken away. By making some assumptions regarding the burdened rate for an RCT and the burdened rate for a worker, the labor costs alone for no show in the sampling period are $2.1 million or, if we assume a job of equal size would have been performed instead, $4.2 million in labor costs. (Note: this metric only looks at labor, and if we factor in the value of the actual work to be performed, the cost of "no shows" may be orders of magnitude larger.) As shown in Figure 16, the graph shows an increasing number of no shows in the beginning of the week and occurring less by the end of the week with only some correlation (R=0.732) to how much work is being performed.

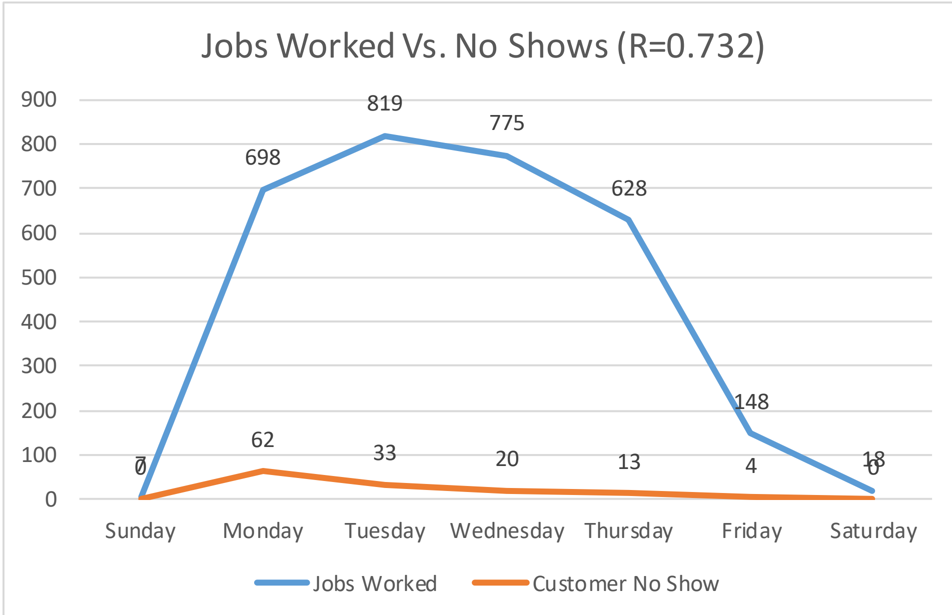


Figure 16: Jobs Worked Vs. No Shows

Again, looking at Figure 17 below, we can see an almost linear relationship between the occurrence of no shows and how late in the week it is.

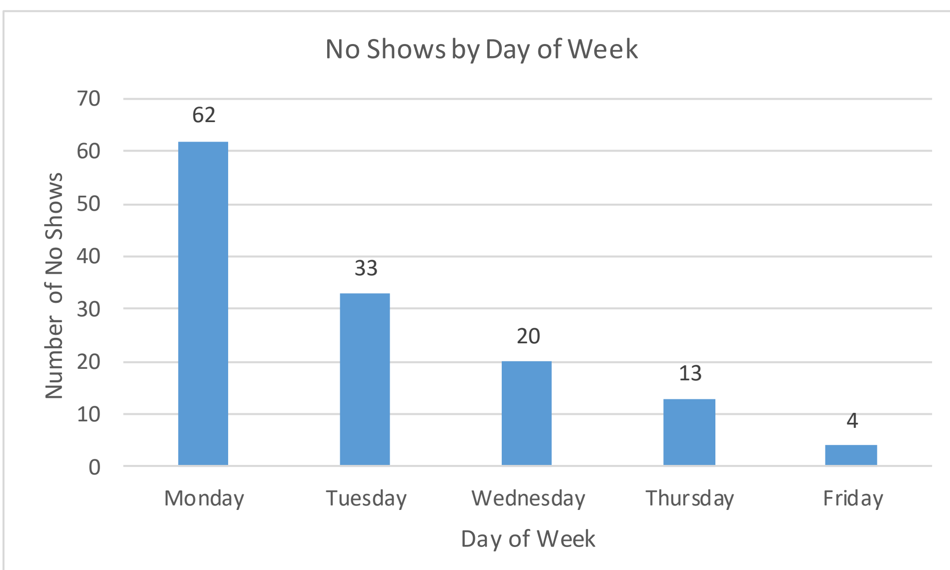


Figure 17: No Shows by Day of Week

Jobs Worked Vs Contamination Detected Exiting RCA

Any well managed radiologically controlled facility (RCA) dealing in radiological contamination practices a philosophy of "defense in depth". This means that certain controls are put in place based on the probability of contamination occurring and the consequences associated with that contamination. It is of particular interest to a health physics group how often contamination is detected at the final boundary. In this case, the final boundary is the exit of the RCA. As shown in the table, there is limited correlation between work that is being performed and contamination being found at the RCA boundary especially when finding contamination at the other two boundaries are fairly well correlated. This may be due to the random nature of legacy particle contamination which is typically more random in nature. In addition, because of the defense in depth philosophy practiced at the facility, contamination being found at an RCA exit is a somewhat rare event that may need a larger evaluation period than one year to understand any underlying relationship.

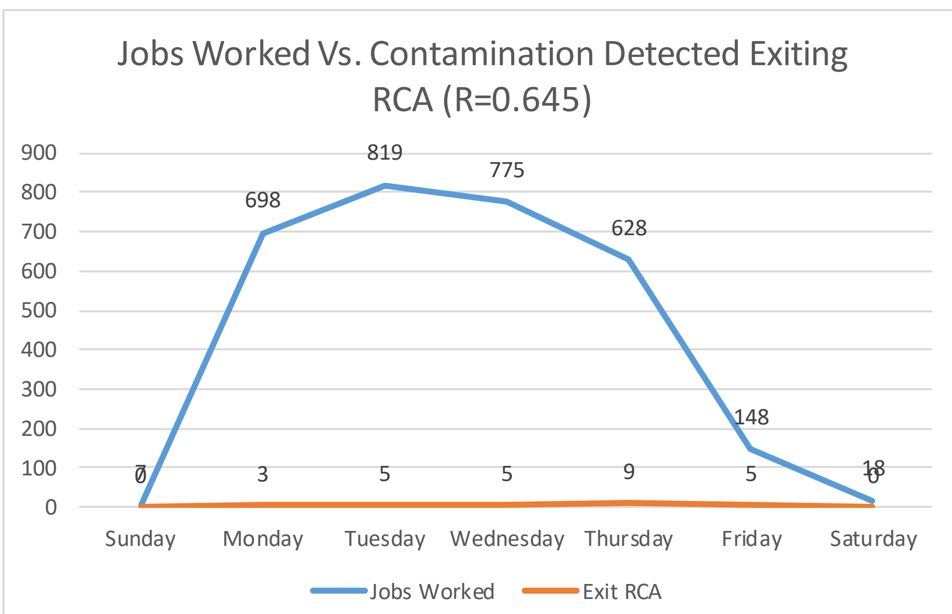


Figure 18: Jobs Worked Vs. Contamination Detected Exiting an RCA

Jobs Worked Vs True CAM Alarms

A Continuous Air Monitor (CAM) is an electronic detector placed in a facility room or near a work area that continuously looks for radioactive material in the air. These are either stationed as permanent fixtures in a room or they may be temporarily relocated during hot work. A true CAM alarm (in contrast to a false CAM alarm) means that some radioactive material was detected above an established threshold value in the air of a room. CAM alarms are enormously expensive since it requires RCTs to respond and close down a room or area.

Looking at the graph below in Figure, the linear correlation is computed to be R=-0.23. In fact, if we try to compare true CAM data to hot work performed, we still only get a marginally stronger correlation with R=-0.15. This is a very surprising finding specifically when we would expect the number of true CAM alarms to be strongly correlated to work being performed.

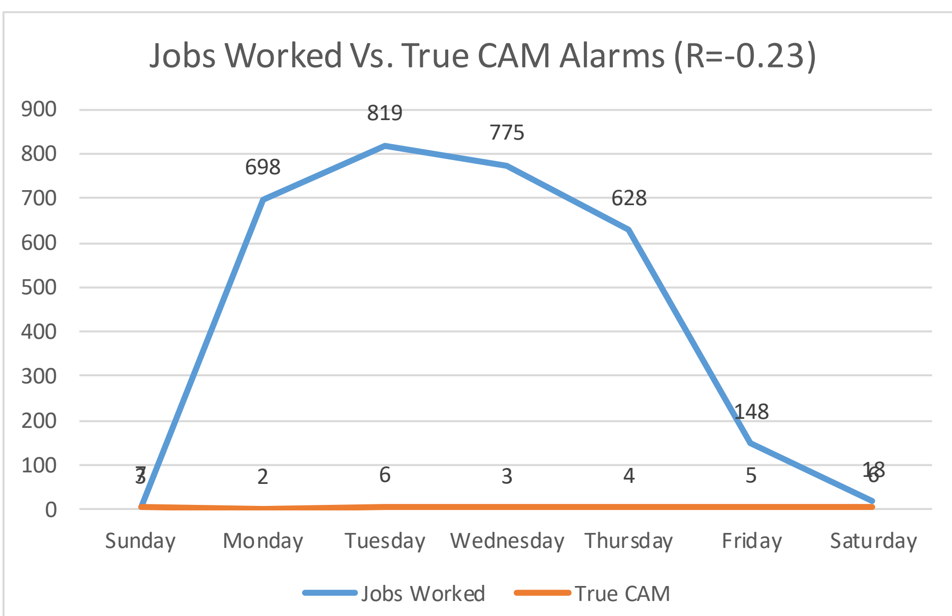


Figure 19: Jobs Worked Vs. True CAM Alarms

Below, in Figure 20, is the data regarding the occurrence of true CAM alarms. The graph shown an almost bimodal distribution peaking around Tuesday and on Saturday.

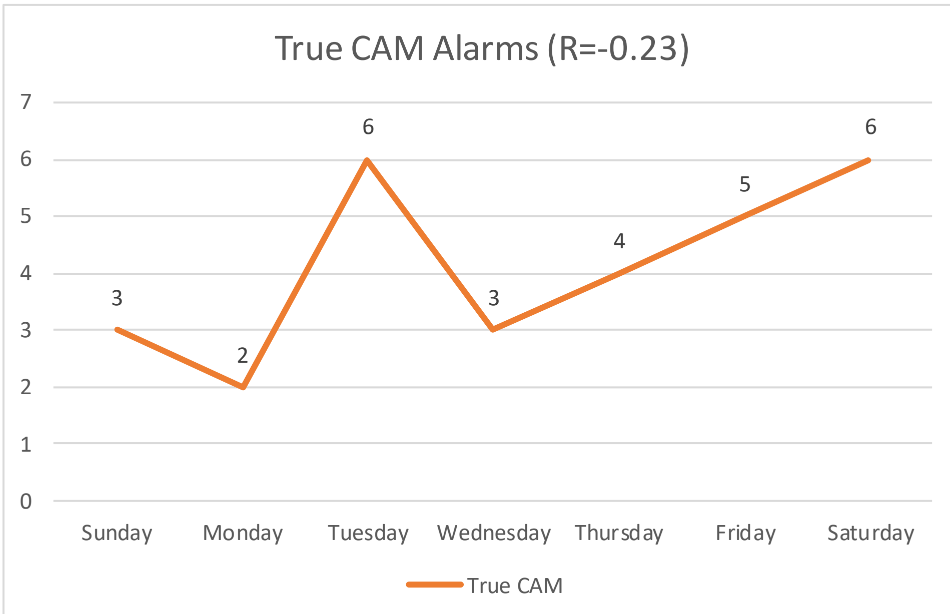


Figure 20: True CAM Alarms by Day of Week

The correlation calculations obviously do not reveal a cause. However, there may be a few opportunities either for optimization or at least consideration. One possible consideration may be that CAM filters are typically changed early in the week. Since the CAM values are set a DAC-hr (a value analogous to an amount of contamination) rather than DAC (a value analogous to a concentration or rate), it may be possible that the CAM alarms are a function of buildup over the week with some of the largest buildup occurring on the weekend. Ultimately, more investigation would be required especially since, as mentioned, the response to true CAM alarms is very expensive.

Opportunities for Optimization

Completion of Hot Work:

Although non-hot work (work that does not involve a respirator) seems to be being completed adequately, accepting 85% as the target we can see from the earlier statistical t-test that we cannot be confident that the same can be said of hot work. As discussed, hot work is high value for the facility.

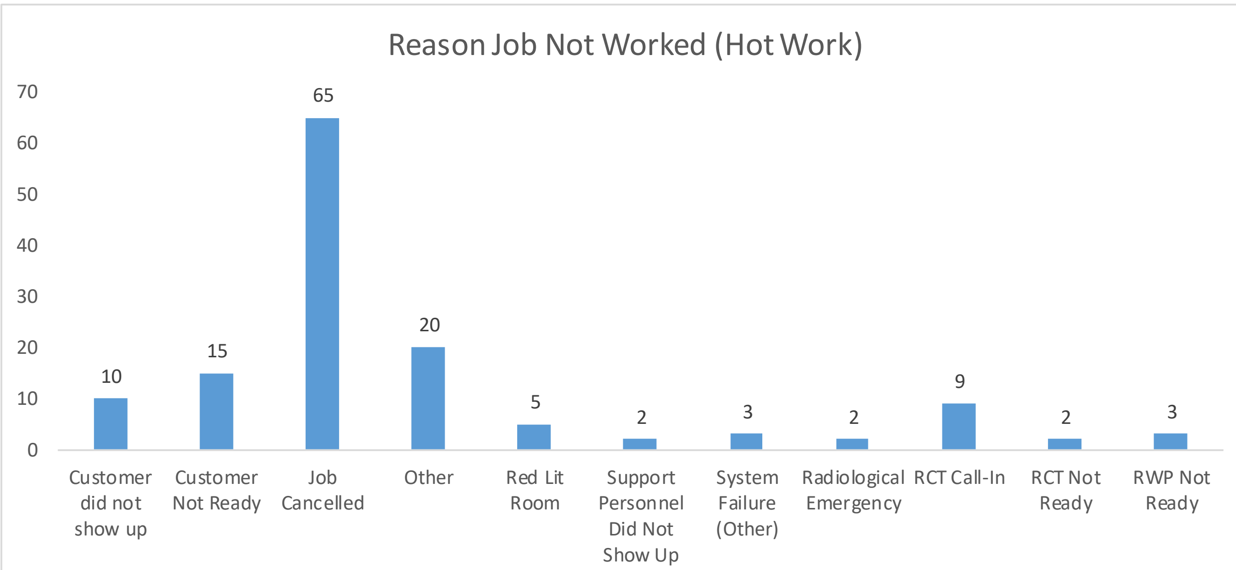


Figure 21: Reasons Jobs Not Worked (Hot Jobs)

Job cancellations (a job was scheduled and then removed from the schedule) plays the largest role with 48% of the total occurrences. Somewhat surprisingly, other was listed as the second most common occurrence with 15% of the total. Schedule adherence would be the target for optimization but more research should be done into why other is chosen and if the collection process is adequately capturing the reasons for cancellations.

Friday Schedule Management:

As discussed earlier and as shown in Figure 13, Fridays tend to be a slower day in the jobs requiring RCT coverage. This is partly due to a work schedule that provides 4-10 schedule where in RCTs and workers tend to work Monday through Thursday at 10 hours each day. However, Fridays tend to have the highest occurrence of job cancellations with 19.6% jobs cancelled to jobs worked ratio due to a variety of reasons shown below in Figure 22.

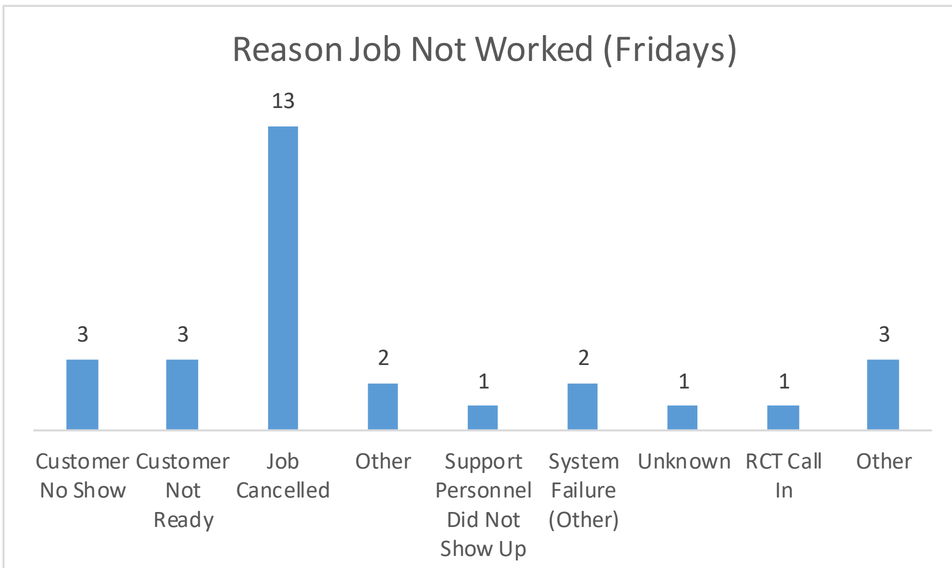


Figure 22: Reasons for Jobs Not Worked (Fridays)

It is somewhat interesting to note that upon further analysis, 100% of the jobs that were not performed were scheduled jobs (as opposed to last minute add-ins to complete a task). More research would need to be done but the target again would be to look at job cancellations with respect to schedule adherence. 13 of the 29 instances listed above (almost 45%) included some form of cancellation of a job listed on the schedule.

No Shows Early in the Week:

As discussed, customers not showing up to perform their work without any notification is a huge problem. Luckily, we can see based on the Figure 16 that this anomaly occurs much more often on Mondays than any other day. Forty-six percent of all no shows occurred on a Monday and roughly 7.5% of anticipated work on a Monday results in a no show. Therefore, work, on Mondays especially, should be targeted for identifying work that is likely to happen or not happen. This could be done through one of several ways including resource meetings early Monday mornings just prior to work starting.

True CAM Alarms on Saturdays:

As discussed, True CAM alarms are unusually likely to occur on Saturdays as compared to other days of the week. More research may need to be performed. It may be due to the fact that higher risk work is performed on Saturdays when there is less work being performed in the facility. In that case, work may be optimized by providing more resources during Saturday work than are already provided in order to prevent CAM alarms and assist in addressing them as necessary. Otherwise, in the case that the true CAM alarms do not occur as result of the work performed, it may be beneficial to evaluate any technical limitations regarding the functioning of the CAMs to resolve any deeper issues resulting in weekend CAM alarms.

Limitations and Areas for Consideration

Challenges regarding the collection of data:

From a statistical standpoint, one of the challenges faced by the facility's RP program trying to take on a project of this scope was ensuring the participation of each of the RCTs in using the forms and having them input their data 100% of the time. This short case study was obviously driven by the RCTs who filled out the forms. Initially, it was believed that the product would ultimately provide a mechanism for the RCTs to establish the very large volume of work they perform especially in comparison to other work groups and that would be motivation enough for the RCTs to participate. However, the product took a great deal of championing on the health physicist's behalf and, as soon as promotion of the product stopped, participation waned. In those cases immediately following the review period captured here, any analysis of the data quickly becomes very poor. One solution may be to somehow create an appropriate random sampling rather than focusing in on trying to achieve 100% participation.

Validation of Data and Models

Models and mechanisms for data validation can and should play an important part of the gathering of data. As mentioned, there is a software package called VSDS that the RCTs use to electronically record their work in documents called surveys. Initially, VSDS was considered as a mechanism for data gathering. However, VSDS did not provide the kinds of metrics we would want to use especially with regard to looking at work groups, durations of the jobs, why work was getting cancelled, etc. so it was rejected for something that could be custom created. That being said though, the data in VSDS could offer a really interesting opportunity baseline the participation in the process highlighted here against this other process and see how the two would compare. For instance, if 90 jobs are completed one particular week based on the pdf form as compared to 100 surveys completed on VSDS, some estimations could be made about the accuracy of one program in relation to the other and see where any information is missing. It may be plausible to even account for that loss systematically but this would take a little bit more time to develop that capability. Ultimately, the process as described here was more of a one way street with RCT providing the information regarding their work where other methods could be explored to create more of a modelling cycle instead where data would be received, VSDS (or other data sources) used to validate, and then that information would be used to optimize the data gathering process.

Limitations Regarding Elementary Statistics

When initially taking on this project, it was initially expected that the problems being taken on to perform the analysis of the data would be pretty similar to the problems typically encountered in a basic statistics class like Math 525. Something learned in participating in this project was how quickly the data and associated data analysis goes from basic into a nonparametric space rather quickly which made it very cumbersome to manage using the tools provided. A good example of this is the t-test illustrated earlier. In that case, we wanted to find a sufficiently sophisticated technique to apply from Math 525 to the analysis here. However, this and other techniques including means, standard deviation, etc., start to abuse the tools and language to a degree when they do not sufficiently model a normal distribution.

Lack of Routine Monitoring Data

Routine monitoring instructions (also referred to as routines, routine surveys, or RMIs) are a significant burden on a radiation protection program in terms of RCT resourcing and costs. Performing routine monitoring is required by most radiation protection programs and there are plenty of opportunities for optimization in this regard. While implementing this process, RMIs were not typically recorded using the form. There are a few reasons for this. One reason is that RMIs can be performed while also performing work and it is a little tricky separating the two for analysis. The second reason is that it would have made the initial implementation of the program more difficult and it was therefore decided to be left out until later. However, if the goal is to optimize the program as a whole, it behooves any program taking on this kind of approach of recording all work performed in the field to incorporate RMIs and the time RCTs spend in those efforts.

Getting the Data Gathering Process Right the First Time:

Finally, the RP program implemented several iterations of the forms used to gather the data in the beginning. From December 2017 through April 2018, there were three revisions of the form before one was settled on as a final form. By changing the form several times, an opportunity to gather several more months of data was missed.

Conclusions

Overall, performing a statistical analysis of this new kind of approach to health physics yielded some really interesting results. Certainly, there is value in using the most basic of tools like means, medians, etc. to more effectively talk about the work performed in radiation protection. Most radiation protection programs as far as I know do not implement a systematic approach to recording and analyzing the work to the same degree that metrics regarding safety issues are managed. However, as we were able to validate to some degree in this project, we can see that there is a very strong connection with regard to how much work is performed and how often those safety issues manifest themselves.

In cases like the worker no shows, using statistics to identify anomalies helps to optimize the safety personnel available and makes the facility safer in that regard. From a monetary standpoint, it is very easy to see how that issue can be specifically targeted. For instance, Mondays have the highest risk of no shows. That issue could be addressed by using the data collected to discipline certain work groups. Different approaches to scheduling can be used where less valuable work would be scheduled earlier in the week and more valuable work scheduled later when the risk of a no show is less. Any of these approaches that works to reduce that risk would be worth millions of dollars in terms of production.

Contrastingly though, some of the statistics really do not support some basic assumptions we have in the field regarding radiation protection. Having true CAM alarms having either no correlation or even an inverse correlation to the work performed in the field is very strange and is something we will continue to explore.

Finally, I believe this project highlighted significant challenges moving forward regarding how we analyze the data. If we want sufficiently analyze and communicate the results of the process in a formal statistical light, we would need to invest more time into a more sophisticated approach such as nonparametric analysis. Otherwise, we risk losing the opportunity to seek out trends, meaning, and value in the data collected.

Attachment 1: Work Performance Fact Sheet

General	
Total Jobs Anticipated	3554
Total Jobs Worked	3093
Percentage of Jobs Worked	87.03%
Total Jobs Not Worked	461
Percentage of Jobs Not Worked	12.97%

Scheduled Work	
Number of Scheduled Jobs (Anticipated)	3339
Percentage Scheduled (Anticipated)	93.95%
Percentage Scheduled (Worked)	86.67%
Percentage Scheduled (Not Worked)	13.33%

Unscheduled Work	
Number of Unscheduled Jobs (Anticipated)	215
Percentage Unscheduled	6.05%
Percentage of Unscheduled (Worked)	92.56%
Percentage of Unscheduled (Not Worked)	7.44%

Hot Work	
Number of Hot Jobs (Anticipated)	779
Percent Hot Jobs Compared to Total Work	21.92%
Percent of Hot Jobs (Worked)	83.44%
Percent of Hot Jobs (Not Worked)	16.56%

Non-Hot Work	
Number of non-Hot Jobs	2775
Percent non-Hot Jobs Compared to Total Work	78.08%
Percent of non-Hot Jobs (Worked)	88.04%
Percent of non-Hot Jobs (Not Worked)	11.96%

Attachment 2: Table of z Scores

NEGATIVE *z* Scores

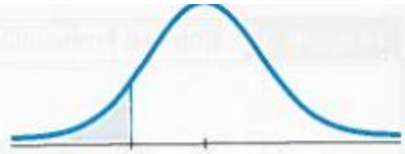
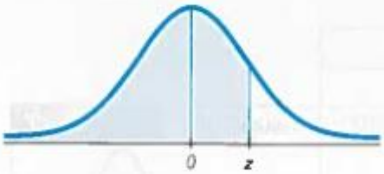


TABLE A-2 Standard Normal (z) Distribution: Cumulative Area from the LEFT

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
−3.50 and lower	.0001									
−3.4	.0003	.0003	.0003	.0003	.0003	.0003	.0003	.0003	.0003	.0002
−3.3	.0005	.0005	.0005	.0004	.0004	.0004	.0004	.0004	.0004	.0003
−3.2	.0007	.0007	.0006	.0006	.0006	.0006	.0006	.0005	.0005	.0005
−3.1	.0010	.0009	.0009	.0009	.0008	.0008	.0008	.0008	.0007	.0007
−3.0	.0013	.0013	.0013	.0012	.0012	.0011	.0011	.0011	.0010	.0010
−2.9	.0019	.0018	.0018	.0017	.0016	.0016	.0015	.0015	.0014	.0014
−2.8	.0026	.0025	.0024	.0023	.0023	.0022	.0021	.0021	.0020	.0019
−2.7	.0035	.0034	.0033	.0032	.0031	.0030	.0029	.0028	.0027	.0026
−2.6	.0047	.0045	.0044	.0043	.0041	.0040	.0039	.0038	.0037	.0036
−2.5	.0062	.0060	.0059	.0057	.0055	.0054	.0052	.0051	* .0049	.0048
−2.4	.0082	.0080	.0078	.0075	.0073	.0071	.0069	.0068	.0066	.0064
−2.3	.0107	.0104	.0102	.0099	.0096	.0094	.0091	.0089	.0087	.0084
−2.2	.0139	.0136	.0132	.0129	.0125	.0122	.0119	.0116	.0113	.0110
−2.1	.0179	.0174	.0170	.0166	.0162	.0158	.0154	.0150	.0146	.0143
−2.0	.0228	.0222	.0217	.0212	.0207	.0202	.0197	.0192	.0188	.0183
−1.9	.0287	.0281	.0274	.0268	.0262	.0256	.0250	.0244	.0239	.0233
−1.8	.0359	.0351	.0344	.0336	.0329	.0322	.0314	.0307	.0301	.0294
−1.7	.0446	.0436	.0427	.0418	.0409	.0401	.0392	.0384	.0375	.0367
−1.6	.0548	.0537	.0526	.0516	.0505	* .0495	.0485	.0475	.0465	.0455
−1.5	.0668	.0655	.0643	.0630	.0618	.0606	.0594	.0582	.0571	.0559
−1.4	.0808	.0793	.0778	.0764	.0749	.0735	.0721	.0708	.0694	.0681
−1.3	.0968	.0951	.0934	.0918	.0901	.0885	.0869	.0853	.0838	.0823
−1.2	.1151	.1131	.1112	.1093	.1075	.1056	.1038	.1020	.1003	.0985
−1.1	.1357	.1335	.1314	.1292	.1271	.1251	.1230	.1210	.1190	.1170
−1.0	.1587	.1562	.1539	.1515	.1492	.1469	.1446	.1423	.1401	.1379
−0.9	.1841	.1814	.1788	.1762	.1736	.1711	.1685	.1660	.1635	.1611
−0.8	.2119	.2090	.2061	.2033	.2005	.1977	.1949	.1922	.1894	.1867
−0.7	.2420	.2389	.2358	.2327	.2296	.2266	.2236	.2206	.2177	.2148
−0.6	.2743	.2709	.2676	.2643	.2611	.2578	.2546	.2514	.2483	.2451
−0.5	.3085	.3050	.3015	.2981	.2946	.2912	.2877	.2843	.2810	.2776
−0.4	.3446	.3409	.3372	.3336	.3300	.3264	.3228	.3192	.3156	.3121
−0.3	.3821	.3783	.3745	.3707	.3669	.3632	.3594	.3557	.3520	.3483
−0.2	.4207	.4168	.4129	.4090	.4052	.4013	.3974	.3936	.3897	.3859
−0.1	.4602	.4562	.4522	.4483	.4443	.4404	.4364	.4325	.4286	.4247
−0.0	.5000	.4960	.4920	.4880	.4840	.4801	.4761	.4721	.4681	.4641

NOTE: For values of z below −3.49, use 0.0001 for the area.
*Use these common values that result from interpolation:

z score	Area
−1.645	0.0500
−2.575	0.0050



POSITIVE z Scores

TABLE A-2 (*continued*) Cumulative Area from the LEFT

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495 *	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949 *	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998
3.50 and up	.9999									

NOTE: For values of z above 3.49, use 0.9999 for the area.
*Use these common values that result from interpolation:

z score	Area
1.645	0.9500
2.575	0.9950

Common Critical Values

Confidence Level	Critical Value
0.90	1.645
0.95	1.96
0.99	2.575

(Triola, 2006)

Bibliography

Triola, M. F. (2006). *Elementary Statistics.* Boston: Pearson Education.